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Measurement of Coughing Capacity and Peak Expiratory Flow Using Smartphone-Based Voice Tool: A New Screening Diagnostic Tool

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ABSTRACT

This study evaluates smartphone-based cough sound analysis as a non-invasive alternative to traditional flow meters for measuring Peak Cough Flow (PCF) and Peak Expiratory Flow (PEF). We compared Coughing Sound Intensity (CSI) measured via a Voice Tools (VT) application across three smartphones (iPhone, Samsung, Xiaomi) against a standard Sound Level Meter (SLM). In 62 healthy adults, significant positive correlations were found between PCF and CSI measured by both SLM ($r = 0.372$, $p = 0.003$) and the iPhone app (VTi) ($\rho = 0.402$, $p = 0.001$). PEF also significantly correlated with huffing sound intensity using SLM, VTi, and Samsung. Among the tested smartphones, VTi demonstrated the strongest predictive value for reduced PCF (60.78% sensitivity, 72.73% specificity) and PEF. While the SLM retained the highest overall sensitivity for predicting reduced PCF (87.5%), the iPhone application provided the most robust smartphone-based correlation. Conclusively, smartphone voice applications, particularly on iOS devices, offer a promising and accessible method to evaluate respiratory function parameters, correlating effectively with standard clinical measurement tools.

Keywords*: Peak Cough Flow; Peak expiratory flow; sound intensity; smartphone*

INTRODUCTION

Peak cough flow (PCF) and peak expiratory flow (PEF) are key respiratory functions routinely measured by peak flow meters in clinical practices. Coughing and huffing both produce sound as air passes through the vocal cords, which can be quantified in decibels using a sound level meter (SLM). In cases where participants cannot cough voluntarily—due to cognitive impairment, unconsciousness, or orofacial defects—or due to unavailability of peak flow meters, PCF and PEF measurements are not feasible. Therefore, alternative objective tools are needed to assess cough function and airflow for pulmonary rehabilitation(Branson, 2013).

Recent advances have explored alternative methods for evaluating cough strength by analyzing cough sounds recorded via microphones, including those integrated into smartphones. Studies have demonstrated a significant correlation between cough sound pressure levels and PCF, suggesting that sound-based measurements could serve as a non-invasive, accessible device for cough flow assessment (Umayahara *et al.*, 2018). This approach influences the widespread availability of smartphones equipped with sensitive microphones, potentially enabling remote or home-based monitoring without the need for bulky or costly instruments.

In this context, comparing the accuracy and reliability of cough and expiratory flow measurements obtained through a smartphone's voice tools app with those from a golden standard of sound level meter, a factory-calibrated instrument designed to measure decibel levels, becomes this research focus. Investigating this comparison could advance the development of practical, user-friendly tools for respiratory monitoring, improving participants' care and facilitating early detection of respiratory decline.

METHODS OF RESEARCH

We conducted 2 cross-sectional studies of observational analysis in order to determine the correlation between PCF and PEF to CSI and HSI, and to have cutoff points of CSI and HSI. Each study included 62 healthy adults that met criteria of age between 18 - 59 years who were accessible at Persahabatan Hospital from January to March 2025, and agreed to participate after proceeding with a written informed consent. We excluded participants with criteria of undergoing treatment for cardiorespiratory disorders, exhibited impaired pulmonary function as indicated by a forced vital capacity (FVC) below 70% of the predicted value, or had vocal cord pathologies marked by dysphonia. Participants who decided to withdraw from the study at any point were categorized as drop-outs.

Data Collection Procedures

Peak expiratory flow (PEF) and peak cough flow (PCF) were measured using a peak flow meter. The device was reset to zero prior to each measurement. Participants were instructed to stand upright, hold the peak flow meter in front of them, and inhale as deeply as possible. The mouthpiece is then placed in their mouth with their lips sealed around it, and their tongue not obstructing the airflow. Participants were instructed to exhale or cough forcefully and quickly into the device. Each test was performed three times, with the highest recorded value used for analysis.

The Protocol of Coughing and Huffing Sound Measurement

Following these measurements, participants were asked to perform huffing and coughing while their vocal sounds were recorded in the soundproof room. Recordings were made using a smartphone with a voice tools application and SLM as the gold standard of the measurement of sound intensity. We demonstrated voice tools in 3 different smartphones, iPhone 15 Pro Max as VTi, Samsung Galaxy S22 Ultra as VTs, Xiaomi type Redmi A2 as VTx. The participants were asked to stand in front of the smartphones and SLM, with the distance between the microphone and the participant's mouth being 20 cm as shown in **Figure 1**. The order of smartphones and SLM from left to right are Samsung, Xiaomi, iPhone, and SLM, respectively. Participants were asked to perform coughing and huffing three times. All sound intensities of coughing and huffing were recorded in decibels (dB). Data analysis uses the highest value of coughing and huffing sound intensity.

Statistical Analysis

Statistical analyses were performed using IBM SPSS Statistics version 26. Descriptive statistics were used to summarize participant characteristics. The normality of data distribution was evaluated using the Kolmogorov-Smirnov test. Data were expressed as mean ± standard deviation for normally distributed variables and as median (minimum–maximum) for non-normally distributed variables.

Diagnostic accuracy was assessed using Receiver Operating Characteristic (ROC) curve analysis, with sensitivity, specificity, and the Area Under the Curve (AUC) calculated. Pearson's or Spearman's correlation tests were applied based on data distribution. Statistical significance was set at $p < 0.05$ with a 95% confidence interval.


Figure 1 **Figure 2** **Figure 3** **Figure 4**

Figure 1. Protocol of Sound Measurement; **Figure 2.** Spectrogram graphic; **Figure 3.** Example result of cough-sound measurement; **Figure 4.** The equipment:
a. Samsung, b. Xiaomi, c. iPhone, d. SLM.

RESULT AND DISCUSSION

1) Correlation Between Coughing and Huffing Sound Intensity with Peak Cough Flow and Peak Expiratory Flow

Correlation analyses were conducted to assess the relationship between peak cough flow (PCF) and peak expiratory flow (PEF) with various cough and huff sound intensity measurements. The results are presented in **Table 1**. PCF showed a moderate positive correlation with cough sound measured using SLM ($r = 0.396$, $p = 0.002$, Pearson), and with cough sound intensity measured by VTi ($\rho = 0.430$, $p = 0.001$, Spearman). A weaker but statistically significant correlation was found between PCF and VTs ($\rho = 0.264$, p = 0.041, Spearman), whereas the correlation with VTx was not statistically significant (ρ = 0.210, p = 0.107, Spearman).

PEF demonstrated the strongest correlation with huffing sound measured using SLM (ρ = 0.497, p 0.000, Spearman). Similarly, PEF was significantly correlated with huffing sound intensity measured by VTi (ρ = 0.381, p = 0.003, Spearman) and VTs (ρ = 0.261, p = 0.044, Spearman). However, no significant correlation was observed between PEF and VTx (ρ = 0.085, p = 0.521, Spearman).

Table 1. Correlation between variables

Variable	r	*p-value*
PCF—Cough sound SLM	0.396	0.002[a*]
PEF—Huffing sound SLM	0.497	0.000[b*]
PCF—Cough sound VTi	0.430	0.001[b*]
PEF—Huffing sound VTi	0.381	0.003[b*]
PCF—Cough sound VTs	0.264	0.041[b*]
PEF—Huffing sound VTs	0.261	0.044[b*]
PCF—Cough sound VTx	0.210	0.107[b]
PEF—Huffing sound VTx	0.085	0.521[b]

PCF: Peak Cough Flow; PEF: Peak Expiratory Flow; VTi: Voice Tools iPhone; VTs: Voice Tools Samsung; VTx: Voice Tools Xiaomi; SLM: Sound Level Meter
[a] Pearson correlation; [b] Spearman correlation; * significant

Diagnostic accuracy

Table 2. Diagnostic accuracy

Parameters	Cut-off value (dB)	Sensitivity (95% CI)	Specificity (95% CI)	(p-value)
CSI SLM—PCF	94	72.73 (39.0 - 94.0)	64.71 (50.1 - 77.6)	0.0095*
CSI SLM—PEF	96	87.5 (61.7 - 98.4)	52.17 (36.9 - 67.1)	0.0175*
HSI SLM—PCF	87	90.9 (58.7 - 99.8)	33.33 (20.8 - 47.9)	0.1896
HSI SLM—PEF	83	68.75 (41.3 - 89.0)	69.57 (54.2 - 82.3)	0.0040*
CSI Iphone—PCF	78	60.78 (46.1 - 74.2)	72.73 (39.0 - 94.0)	0.0103*
HSI Iphone—PEF	75	71.74 (56.5 - 84.0)	50.00 (24.7 - 75.3)	0.0319*
CSI Samsung—PCF	76	68.63 (54.1 - 80.9)	63.64 (30.8 - 89.1)	0.0889
HSI Samsung—PEF	65	65.22 (49.8 - 78.6)	62.50 (35.4 - 84.8)	0.0107*
CSI Xiaomi—PCF	81	31.37 (19.1 - 45.9)	90.91 (58.7 - 99.8)	0.1599

HSI Xiaomi—PEF	77	36.96 (23.2 - 52.5)	75.00 (47.6 - 92.7)	0.7498

CSI: Cough Sound Intensity; HSI: Huff Sound Intensity; PCF: peak cough flow; PEF: Peak Expiratory Flow; SLM: Sound Level Meter.

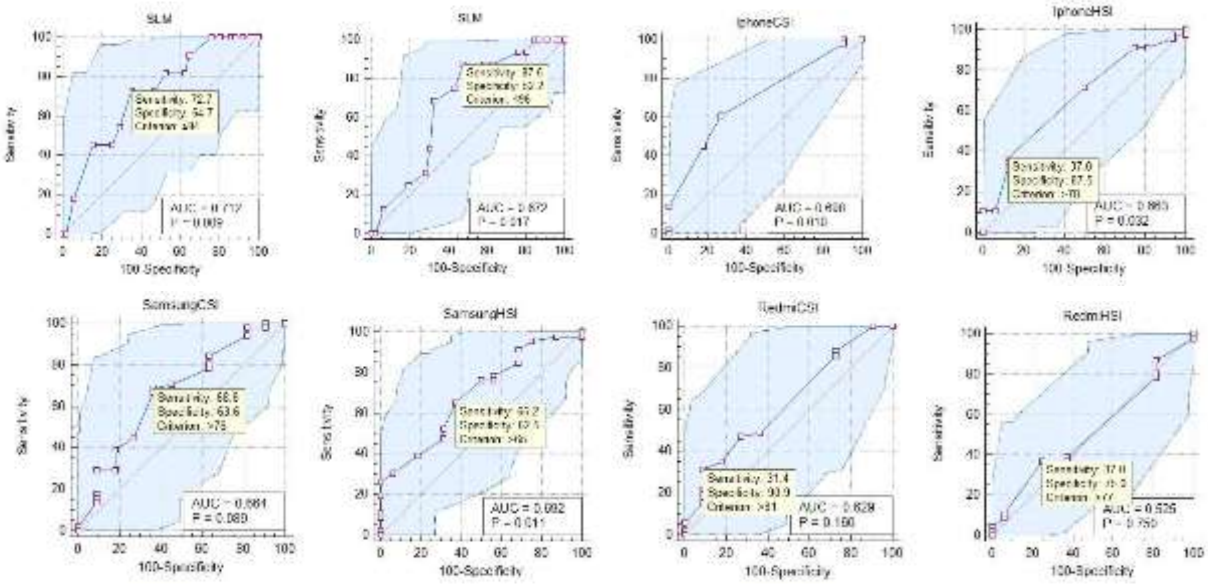

Figure 5. Diagnostic test accuracy.
a. CSI SLM—PCF, b. HSI SLM—PEF, c. CSI Iphone—PCF, d. HSI Iphone—PEF, e. CSI Samsung—PCF, f. HSI Samsung—PEF, g. CSI Xiaomi—PCF, h. HSI Xiaomi—PEF

This study is a correlational and diagnostic study examining the relationship between PCF and PEF with CSI and HSI. The main advantage of this study compared to previous research is that it provides cutoff values for each measurement. In addition, this study also compares cough and huffing sound intensity using a sound level meter, which is considered the gold standard for measuring sound intensity. PCF and CSI as measured by an iPhone (VTi) ($r = 0.430$, $p = 0.001$) and an SLM [$r = 0.396$, $p = 0.002$] were found to be significantly positively correlated in this study. These results imply that coughing's acoustic properties, in particular sound pressure, could be a good indicator of expiratory force. The viability of employing smartphone-based sound recording as an affordable, easily accessible method to track cough intensity in both clinical and non-clinical contexts is supported by this correlation (Sharan *et al.*, n.d.; Xu *et al.*, 2022). Recent research has shown that, with the right microphone placement and signal processing, cough sound analysis on mobile devices can accurately estimate pulmonary function parameters like FEV_1 and PCF, with R2 values as high as 0.94 and error rates under 10% (Umayahara *et al.*, 2018; Xu *et al.*, 2022). These techniques demonstrate promise for remote respiratory assessment using common consumer smartphones and are reliable across age and sex groups (Rudraraju *et al.*, 2020).

However, because huffing has unique acoustic characteristics. Huffing is distinguished by a longer, smoother airflow with lower acceleration and less sound intensity than coughing, which produces a brief, explosive burst with high expiratory acceleration without any glottic closure (Monge-Álvarez *et al.*, 2018). Due to these characteristics, huffing is more challenging to identify and measure precisely using smartphone microphones, which are usually designed to record brief, high-energy acoustic events like coughing (Kvapilova *et al.*, 2019; Umayahara *et al.*, 2018). This may also explain the weaker and less consistent correlation between huffing sound intensity and airflow parameters (PCF and PEF) observed in this study, as the variability in huffing effort and sound makes it less reliable as a surrogate for peak flow measurement.

The superior performance of cough and huffing sound intensity measurements on iPhones compared to Samsung and Xiaomi devices can be attributed to several technical factors. The differences of hardware between those smartphones may influence the sensitivity of the internal microphone of the smartphone. iPhones use high-quality, consistently calibrated microphones with a wide dynamic range and better frequency response, supported by advanced audio processing algorithms that preserve signal clarity. In contrast, many Android devices apply aggressive noise suppression or have variable hardware quality, leading to reduced peak intensity capture and lower signal-to-noise ratio. This results in more reliable and accurate measurements on iPhones, which is crucial for diagnostic purposes. Another research by Umayhara 2018 also showed that iPhone can be a proper protocol for measuring cough sound on mobile, although it was not compared to the gold standard of SLM (Umayahara *et al.*, 2018).

The diagnostic performance of the acoustic parameters varied depending on the outcome (PCF or PEF) and the measurement device used. Among the parameters tested, the HSI using a smartphone for predicting reduced PCF showed the highest sensitivity at 90.9%. However, it had low specificity (33.3%) and did not reach statistical significance ($p = 0.1896$), limiting its diagnostic utility. In contrast, CSI from the iPhone demonstrated a more balanced performance for PCF prediction, with a sensitivity of 60.78% and specificity of 72.73%, and the result was statistically significant ($p = 0.0103$), indicating its potential as a moderately accurate screening tool.

When predicting reduced PEF, the Sound Level Meter (SLM) showed strong performance, achieving high sensitivity (87.5%) with moderate specificity (52.17%) and a significant p-value ($p = 0.0175$), suggesting good utility in identifying individuals with compromised expiratory flow. Similarly, HSI from the iPhone showed acceptable sensitivity (71.74%) but lower specificity (50.0%) for PEF, with statistical significance ($p = 0.0319$). Interestingly, the HSI parameter from non-phone sources performed better for PEF than for PCF, yielding a sensitivity of 68.75% and specificity of 69.57% ($p = 0.0040$), indicating a more balanced and statistically reliable diagnostic profile. Another study performed by Recasens et al (2023) with a focus in peak cough flow only achieved higher diagnostic accuracy with sensitivity 94% and specificity 100% compared to this study. This study also uses a smartphone-based app to detect peak cough flow in participants with neuromuscular disease (Recasens *et al.*, 2024). A case report by Kang et al (2021) showed that cough sound can be recorded by smart devices, so it can be applied to remote participants' monitoring in telemedicine.

The findings of this study can be further explained by the physiological mechanism of sound production, specifically the Myoelastic-Aerodynamic (MEAD) theory initially proposed by van den Berg in 1958. According to this theory, vocal cord vibration is passively generated by the interaction between aerodynamic forces from the lungs and the biomechanics of the vocal cords. Producing a loud cough sound requires a substantial airflow from the lungs and a strong adduction of the vocal cords to build high subglottic pressure. This physiological concept is supported by a study from Izadi et al., which demonstrated that higher subglottal pressure strongly correlates with increased sound intensity (Pavesi *et al.*, 2001). Therefore, a stronger expiratory effort, reflected in higher PCF and PEF values, naturally generates the high subglottal pressure needed to produce the louder sound intensities captured by the smartphone microphones.

Furthermore, the accuracy and clinical application of acoustic measurements are influenced by technical setups and demographic variations. A previous study by Lee et al. (2017) found a strong correlation between sound intensity and cough flow (Spearman's r = 0.87–0.88), but importantly noted that this correlation changes with the distance of the microphone. This justifies the standardized 20 cm distance implemented in our measurement protocol. The reliability of the Voice Tools application utilized in this study is also supported by Booger et al., who validated the application against the Lingwaves gold standard, showing a high correlation ($r > 0.9$, $p < 0.001$) for assessing sound intensity and frequency. Finally, acoustic analysis has proven useful for determining clinical cutoff points; for instance, Li et al. (2024) found that a cough sound intensity below 86.77 dB is an optimal threshold for estimating extubation failure. These factors, along with physiological differences in vocal cord size and respiratory muscle strength across different ages and genders, emphasize the potential of smartphone-based voice tools as a valid diagnostic screening method when properly standardized.

CONCLUSION

This study demonstrates the potential of smartphone based voice tools as a screening diagnostic tool to measure PCF and PEF. The value of the cutoff point achieved from this study could become a referral value when using this protocol of measurement in pulmonary rehabilitation programs. Future research could be conducted using a different protocol that might show a stronger correlation.

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